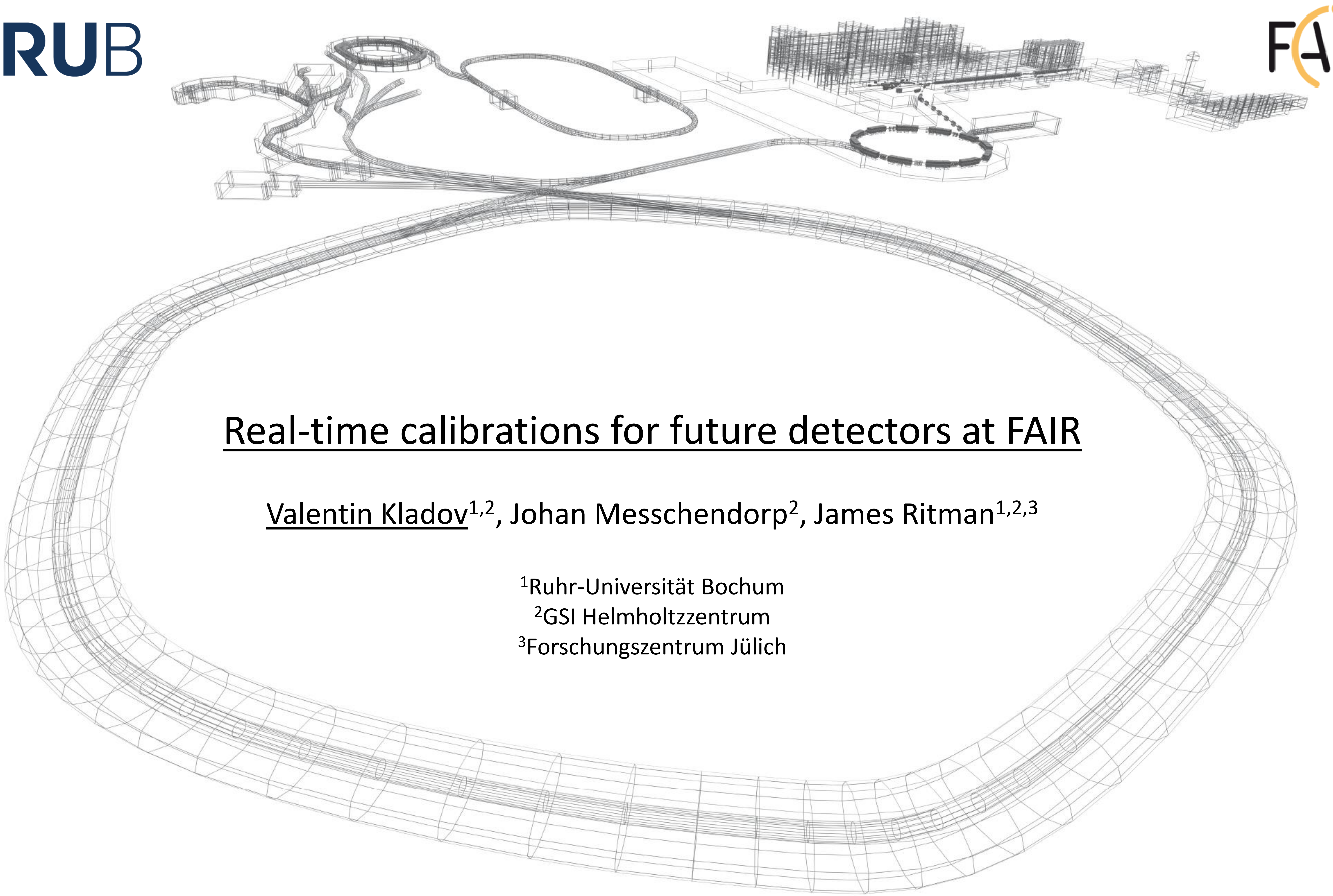


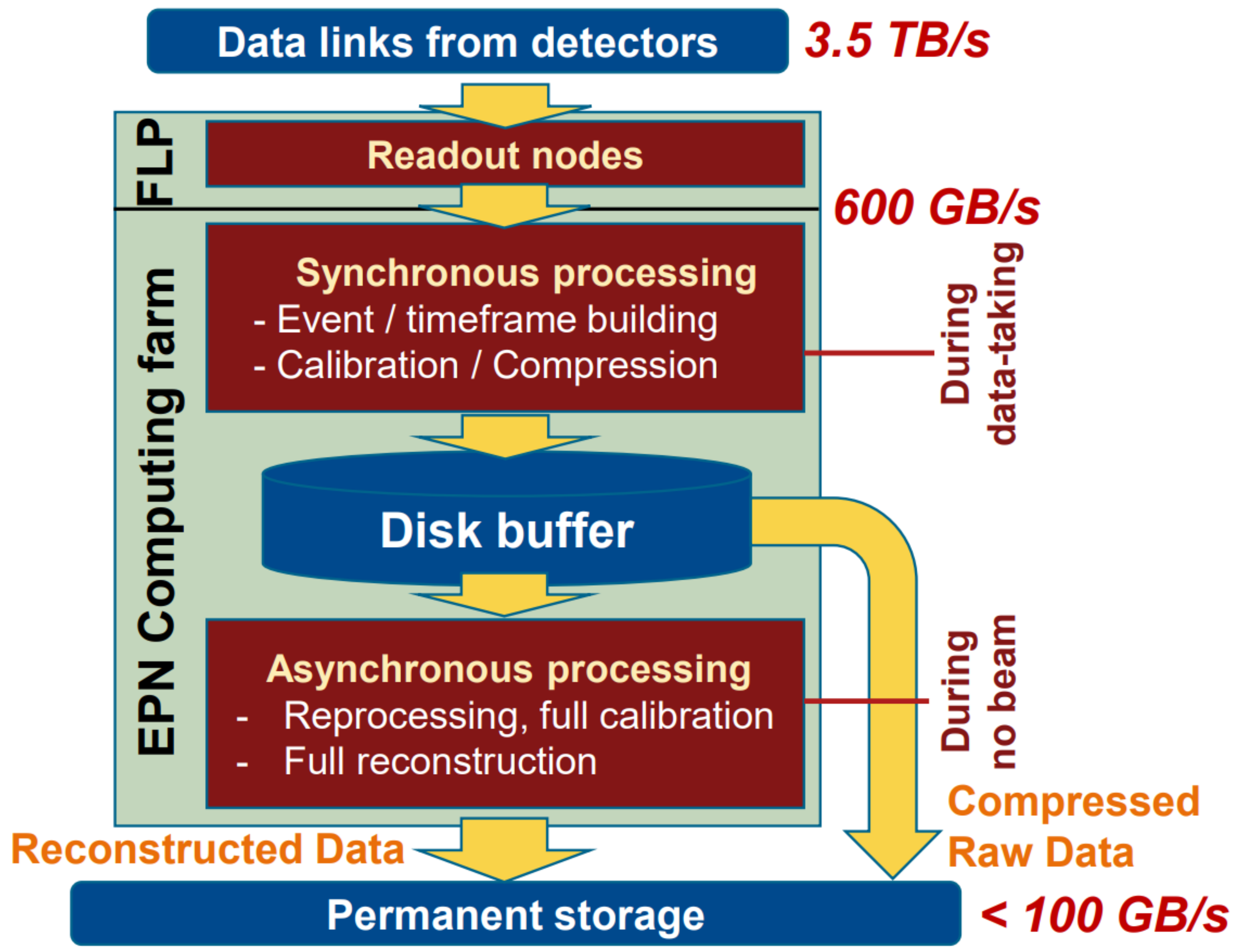
Real-time calibrations for future detectors at FAIR

Valentin Kladov[1,2], Johan Messchendorp[2], James Ritman[1,2,3]

[1]Ruhr-Universität Bochum
[2]GSI Helmholtzzentrum
[3]Forschungszentrum Jülich

Real-time reconstruction and calibration

Online data processing



Processing step	Relative time
TPC Processing (Tracking, Clustering, Compression)	99.37%
EMCAL Processing	0.20%
ITS Processing (Clustering + Tracking)	0.10%
TPC rANS Encoding	0.10%
ITS–TPC matching	0.09%
MFT Processing	0.02%
TOF Processing and Global Matching	0.02%
Rest	0.1%

- Synchronous reconstruction – compress the data from e.g. 600 to 100 GB/s.
- Need fast and precise reconstruction.

- Calibrations need reconstructed tracks.
- Reconstruction needs calibration of tracking.

- Can we avoid the loop?

https://doi.org/10.1051/epjconf/202429505022 - *The O2 software framework and GPU usage in ALICE online and offline reconstruction in Run 3*

Real-time reconstruction and calibration

Challenge

Online reconstruction
for high level online triggering

<u>Online calibrations</u>

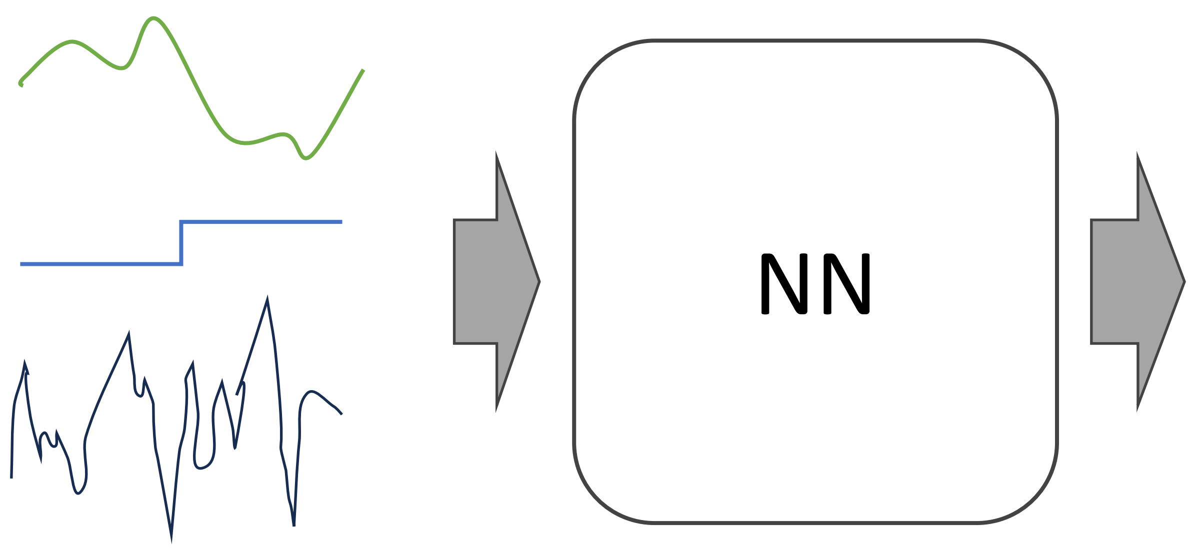
Delays - Calibrations with events take a lot of time

Solution

Environment (P, T)

Settings (V, beam)

Trigger rates



- Calibration factors
- Recommended settings (HV)
- Anomaly detection

Existing approaches

ALICE :
Time projection chamber’s drift velocity (Run2).

- Analysis of reconstructed events;
- Runs on 170 computing nodes for ~2 minutes for required precision.

Mikolaj Krzewicki et al 2017 J. Phys.: Conf. Ser. 898 032055

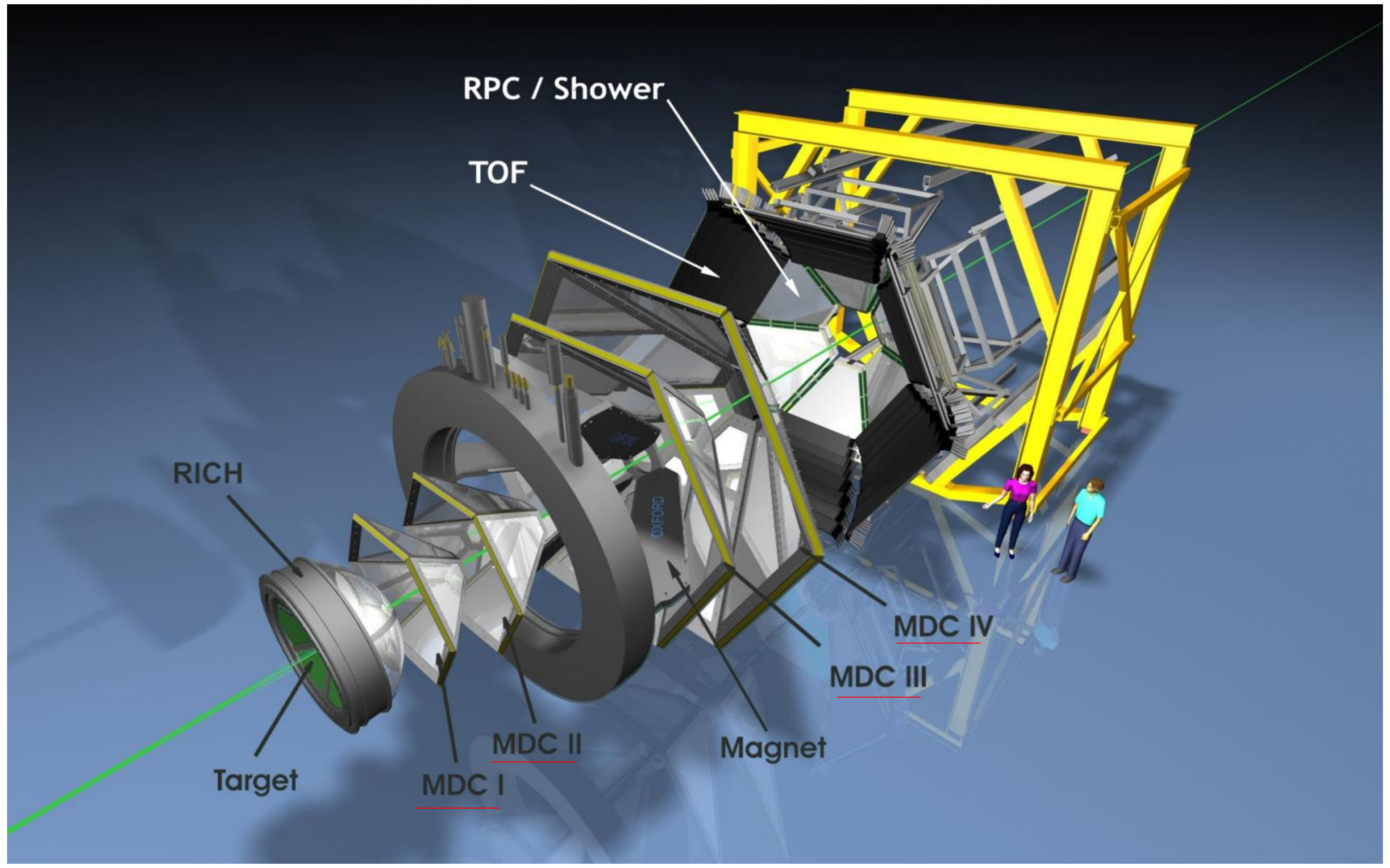
GlueX:
Drift chamber’s global gain;

- NN predictions;
- simple network, fast results.

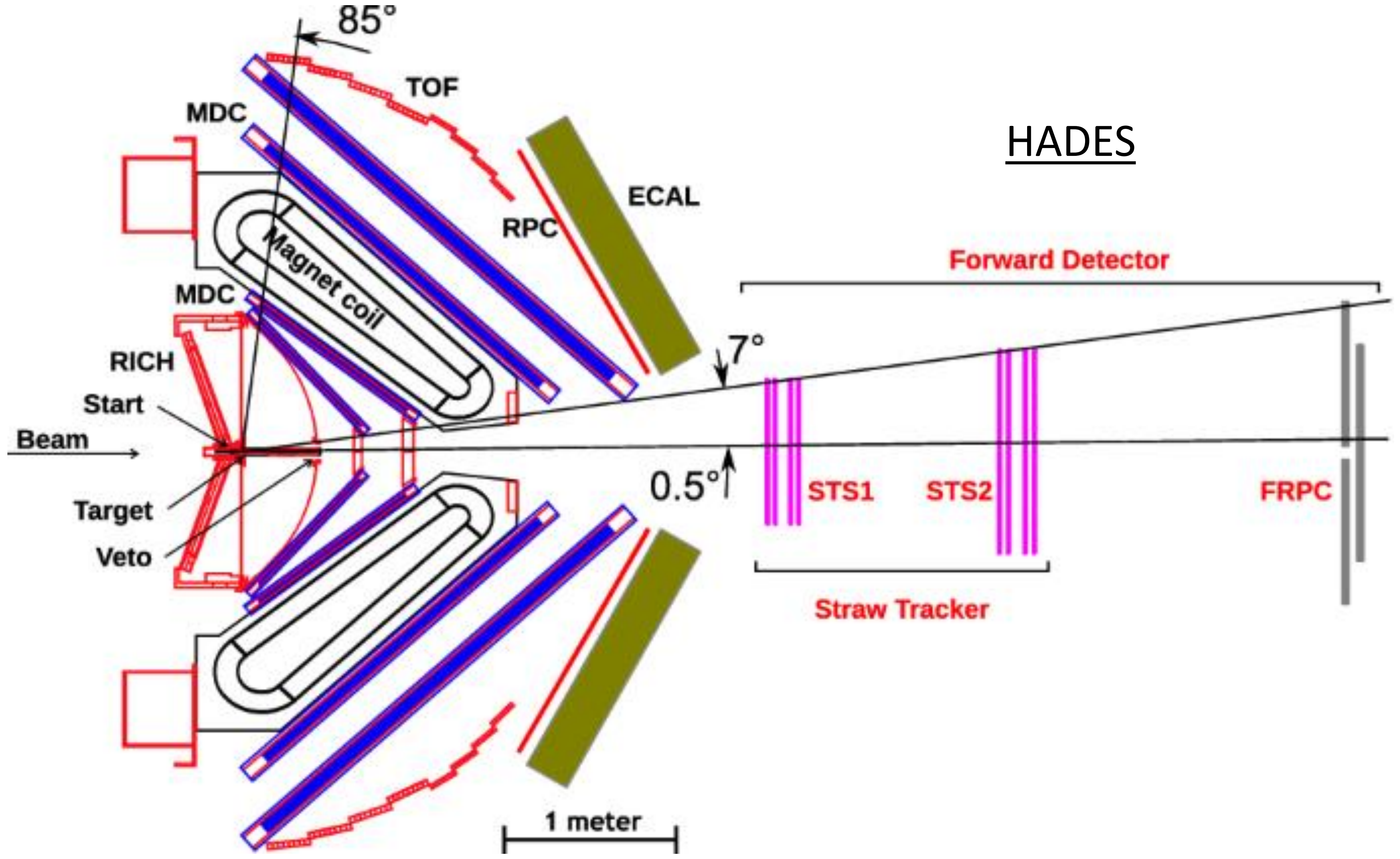
arXiv:2203.05999v1 [physics.ins-det] 11 Mar 2022

HADES experiment as a pilot study for FAIR experiments

- FAIR Phase Zero experiment;
- Currently running with regular data taking (every 1-2 years);
- Developed infrastructure;



4 planes x 6 sectors of MDC = 24 chambers



MDC – mini drift chambers

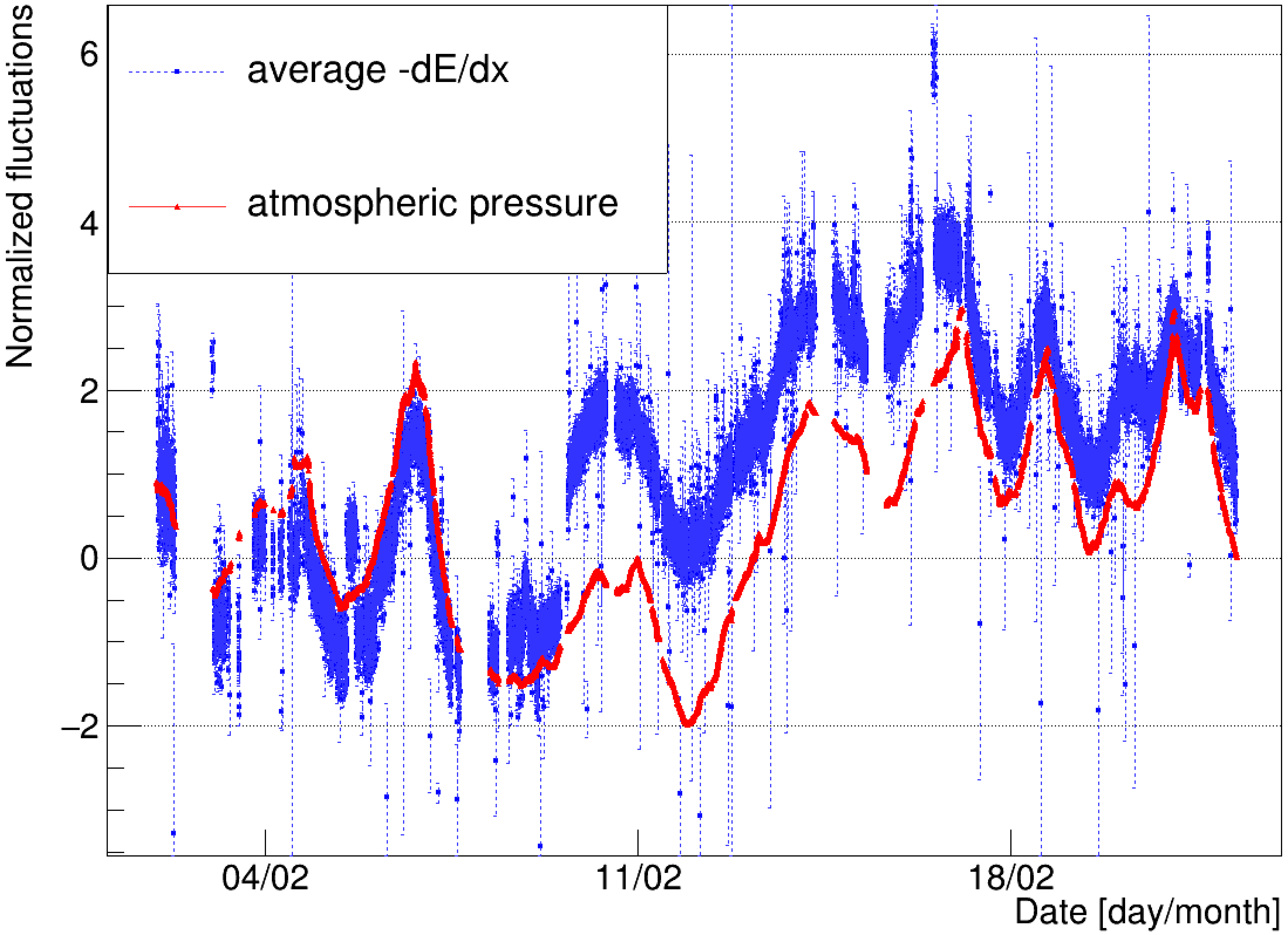
Possible values to predict:

- Drift time (~"measured" distance) – used for track reconstruction.
- Chamber gain (~"measured" dE/dx). – used for PID

Ionization losses in drift chambers

Reasons to test on MDC:

- Significant fluctuations (5-10%);
- Clear dependence on environmental parameters;
- Environmental parameters are measured and stored.



Correlations between atmospheric pressure (red) and averaged ionization losses (blue). Feb22.

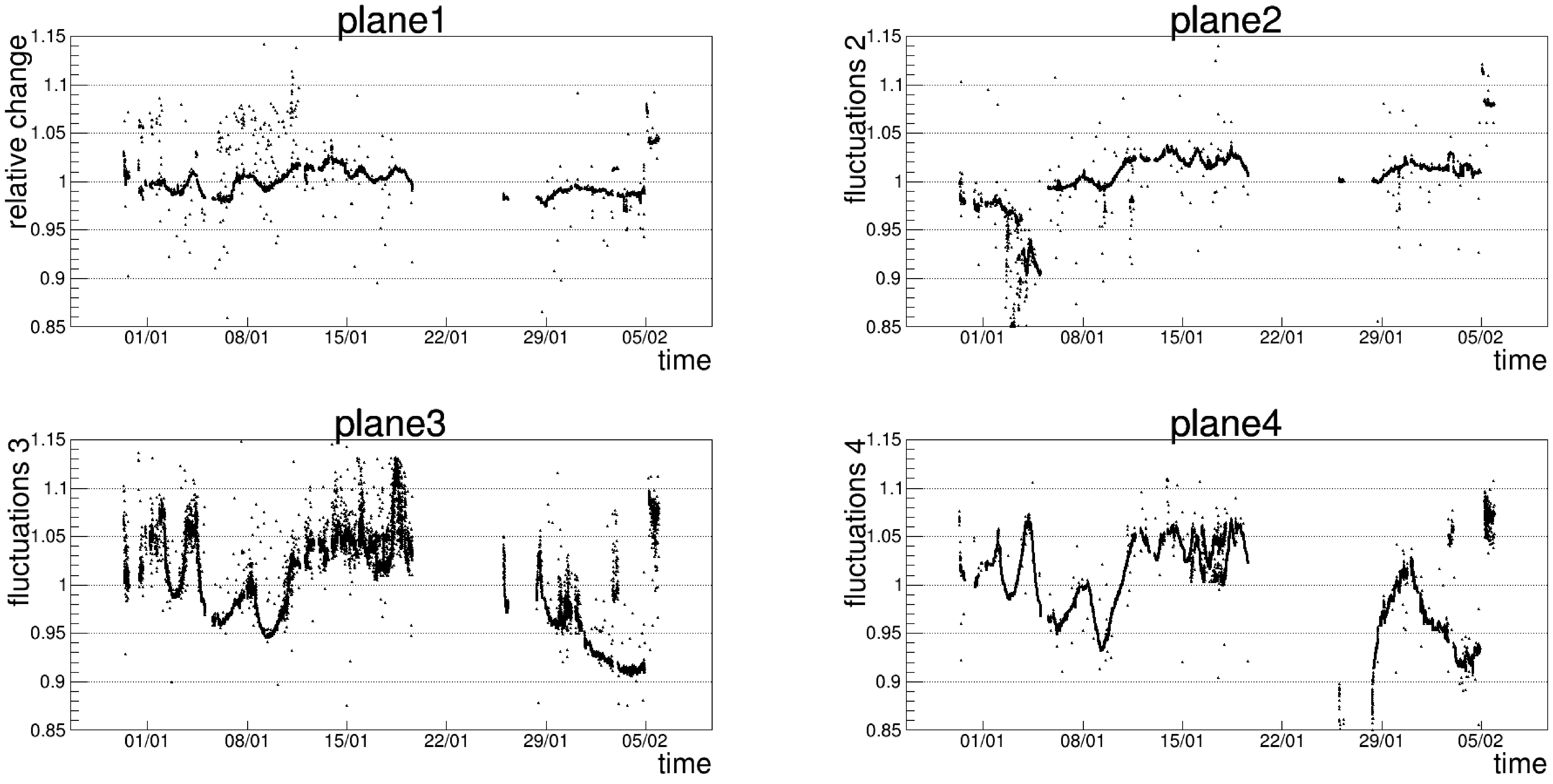
Each dot is a single run, ~100k/24 events, 1-2 min

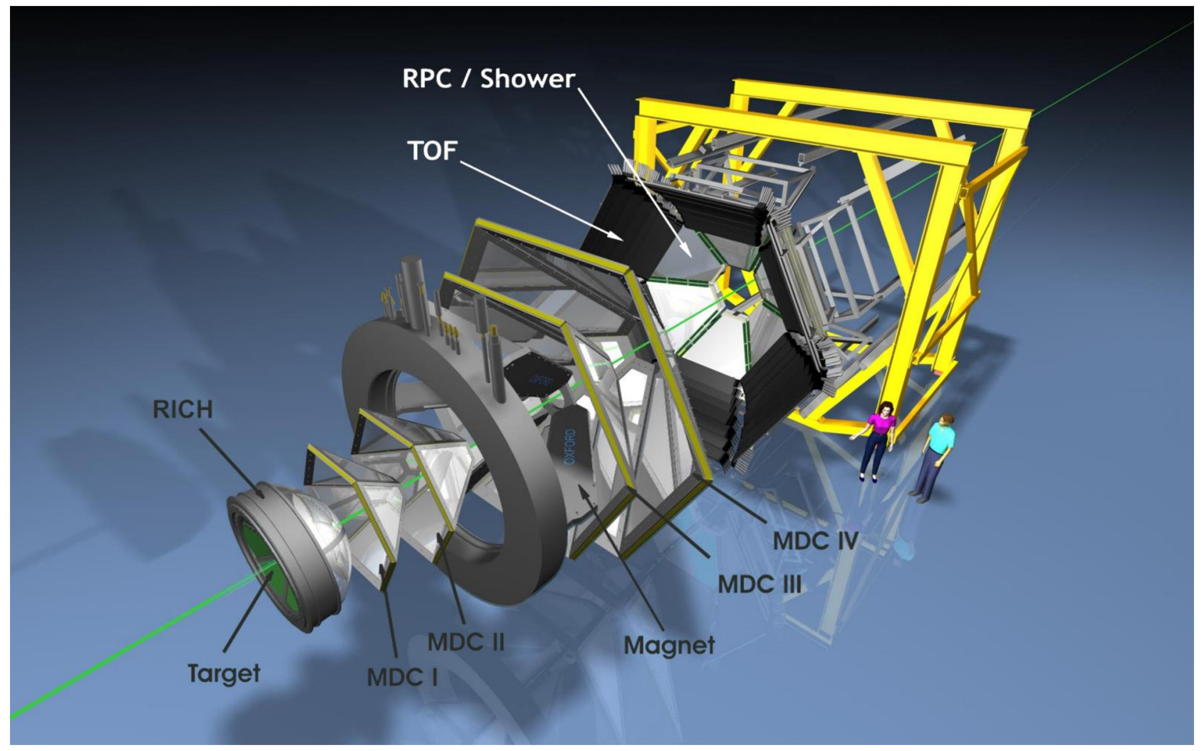
Smooth change with time (~15 min).

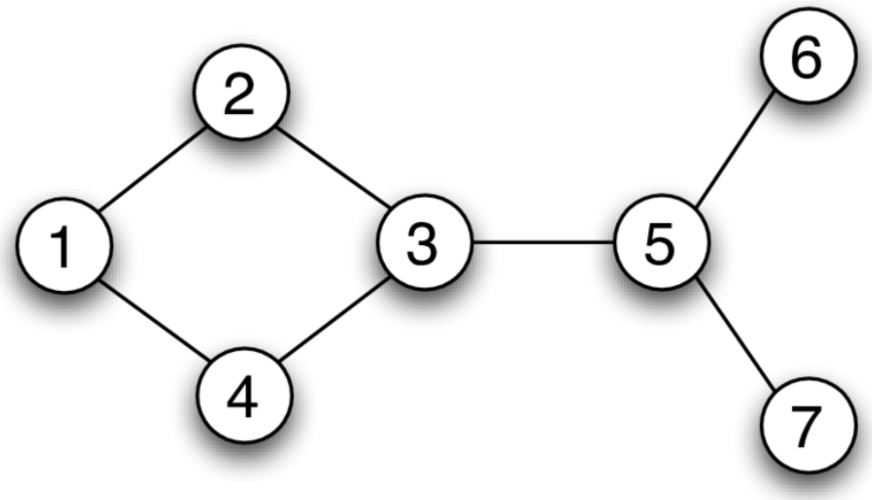
Input parameters:

- Atmospheric pressure;
- High voltage;
- CO_2 concentration;
- Overpressure;
- H_2O concentration;
- Dew Point;
- Electronics temperature;

Multi-channel prediction







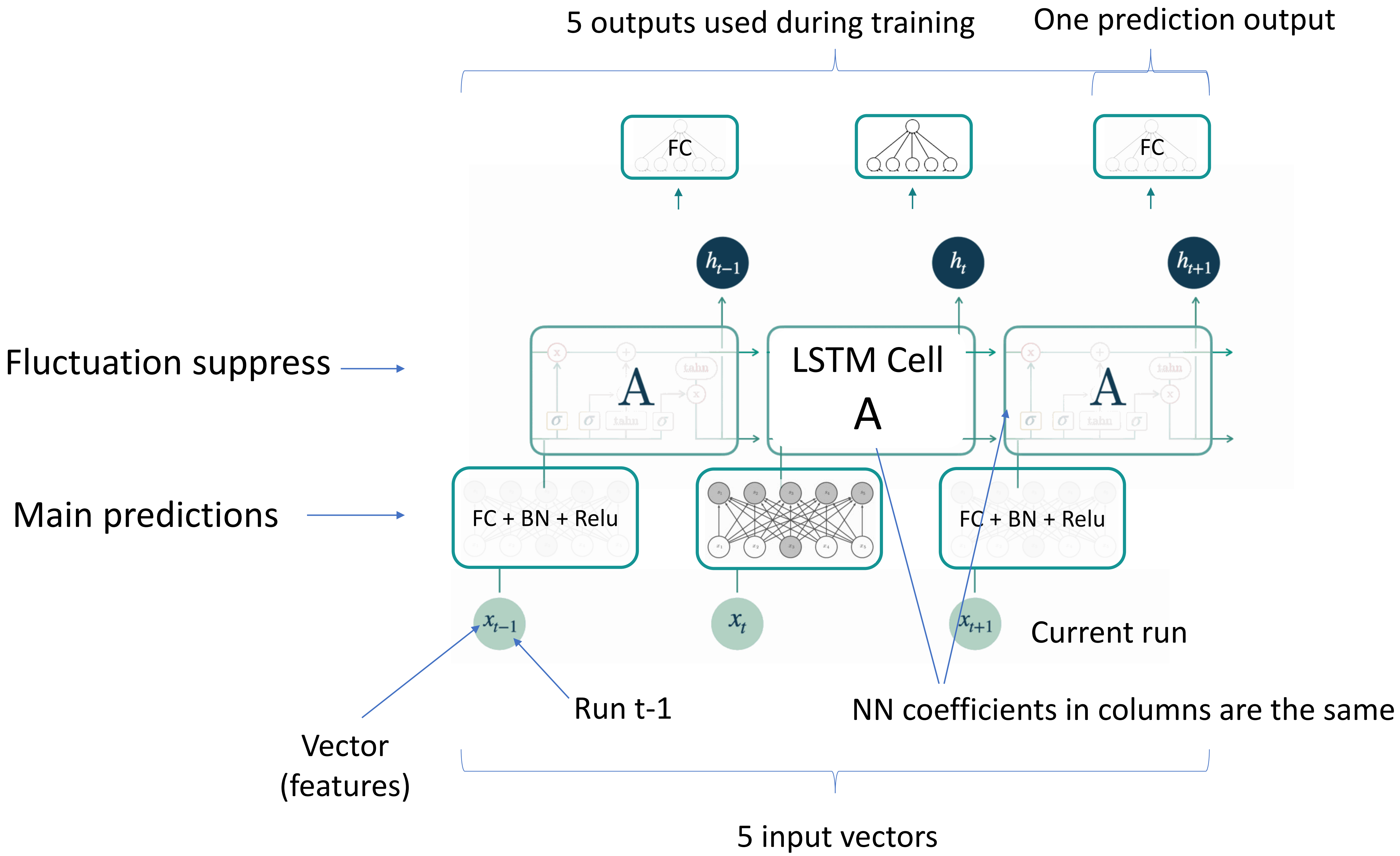
- In general, MDC sectors behave similarly.
- Need to account for the differences.
- Some input parameters are shared (Atm. pressure).

→ Represent detector as a graph for the universality of data handling.

→ Utilize similarities by convolutions.

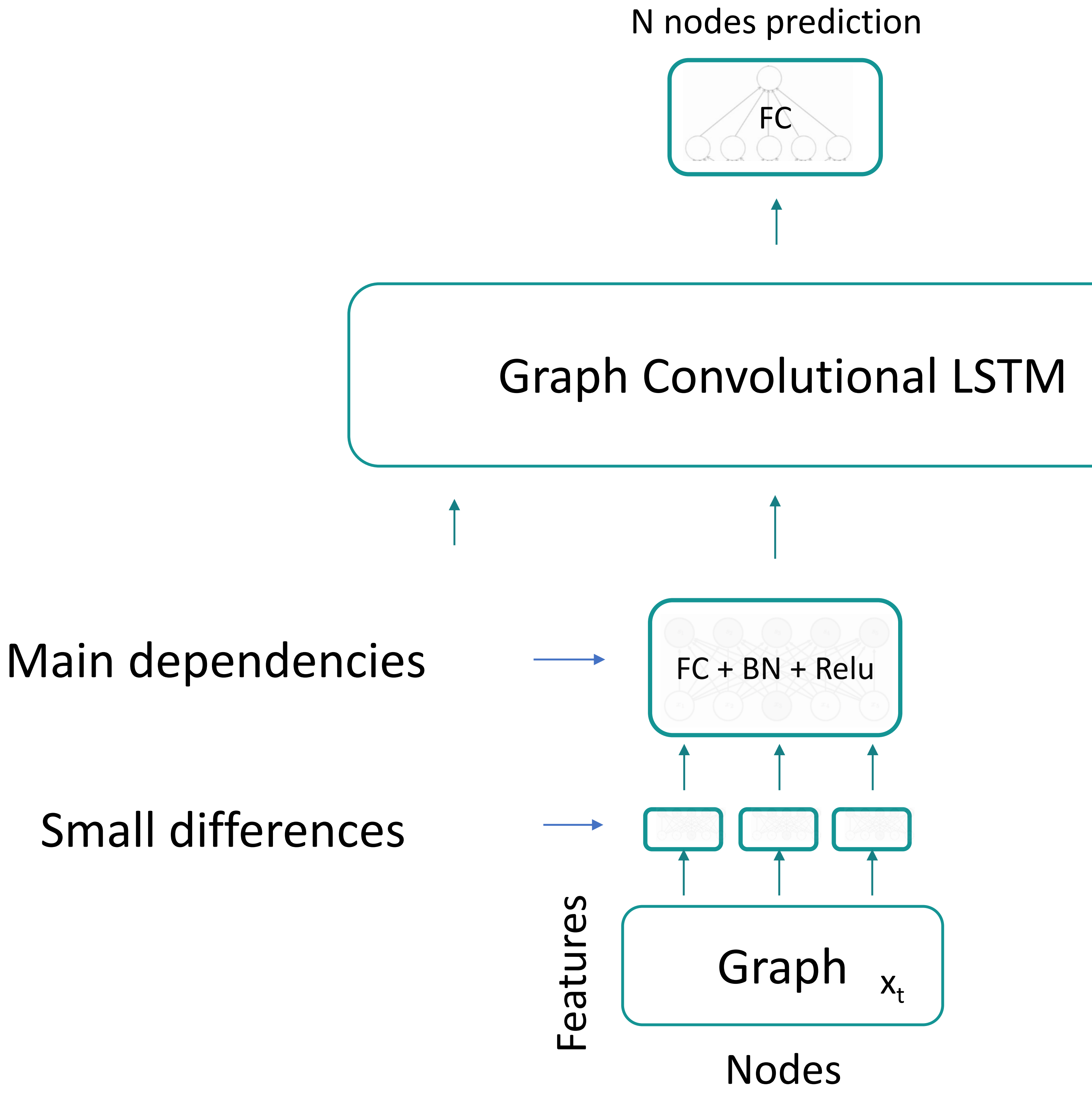
Neural network architecture

Single parameter prediction



Utilizing the smoothness of the environment change

Multi-channel prediction



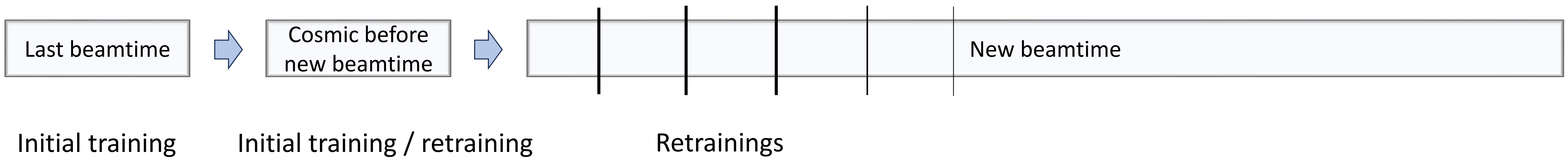
Utilizing similar behavior between channels

Prediction time consumption

Source	Depends on	Time
NN Computation speed	NN propagation $O(N_{nodes})$	$50 \pm 10\ ms$ (24 nodes)
Database readout from GSI network	$\sim(N_{nodes})$	$1 \pm 0.1\ s$ (24 nodes)
Standard run duration (1 data point)	-	$1 - 2\ min$
Environmental parameter stability interval	-	$\sim 15\ min$
NN initial training	$O(N_{epochs} * N_{nodes} * N_{runs})$ + Init	$\sim 30\ min$ (150 epochs, 24 nodes, 10^3 runs)
NN retraining	$O(N_{epochs} * N_{nodes} * N_{runs})$ + Init	$\sim 1\ min$ (50 epochs, 24 nodes, 10^2 runs)

Assuming: T_{change} of inner working of the detector $\gg T_{change}$ of environmental parameters

<u>Retraining scheme:</u>



Can retrain at any time as soon new batches of data are available without any interference with predictions!

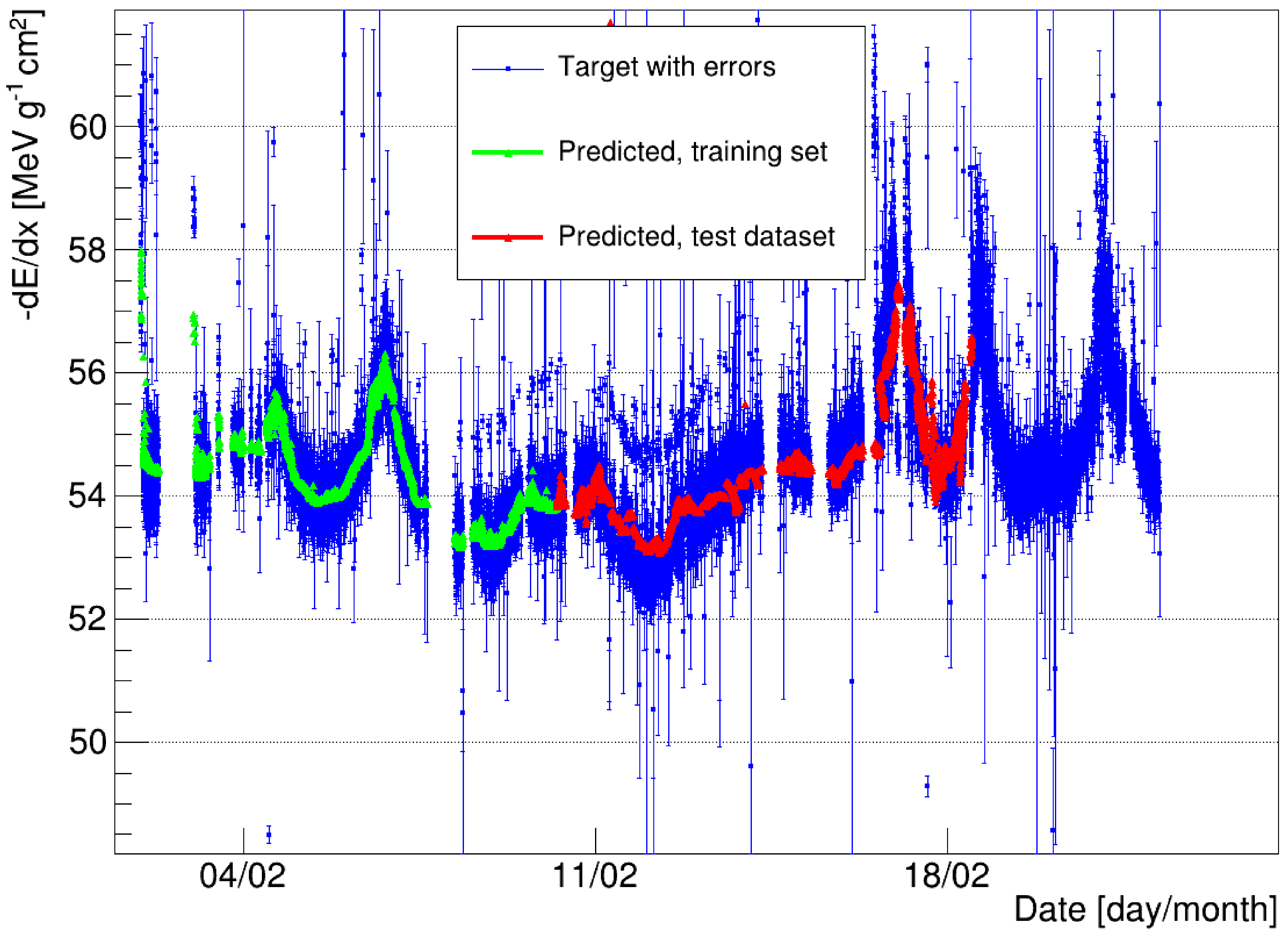
Prediction quality

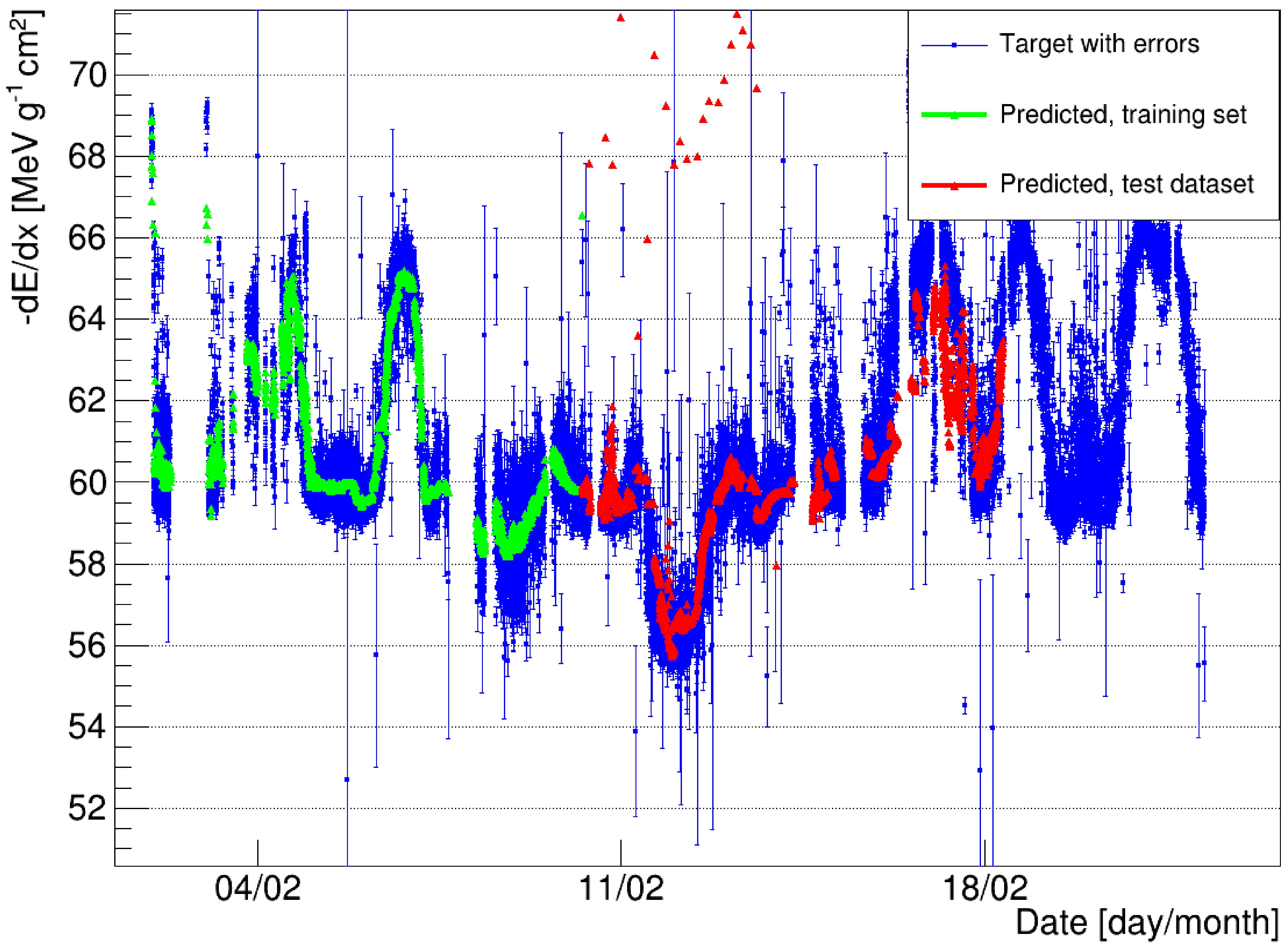
Simulating new beamtime:

1. Get average dE/dx from offline calibration in feb22 data;
2. Train on the part of data, fix most of the parameters after;
3. Predict with added regularization and regular retrainings.

When trained without LSTM and Convolutions:

Stability is the main weak point here.

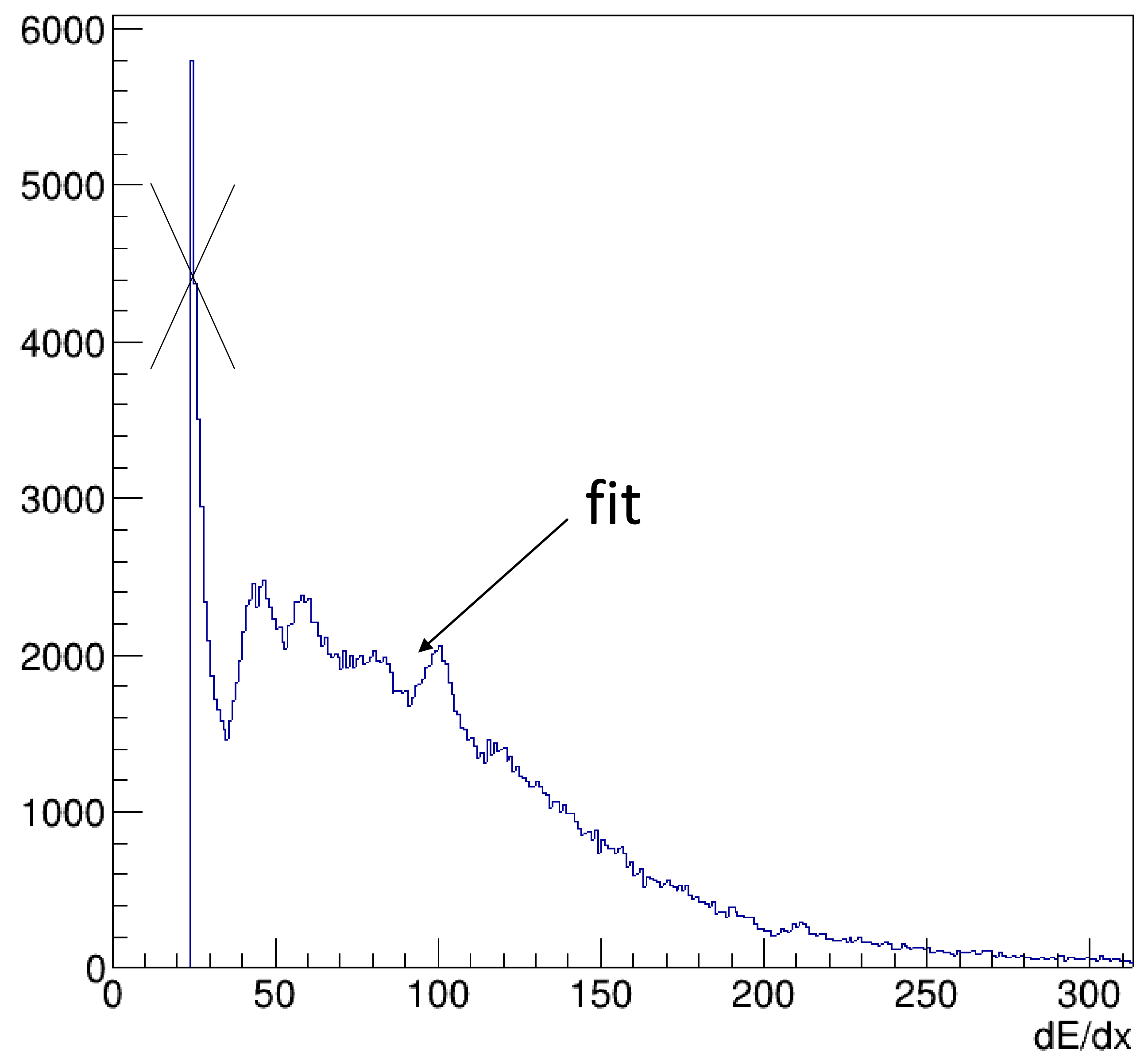


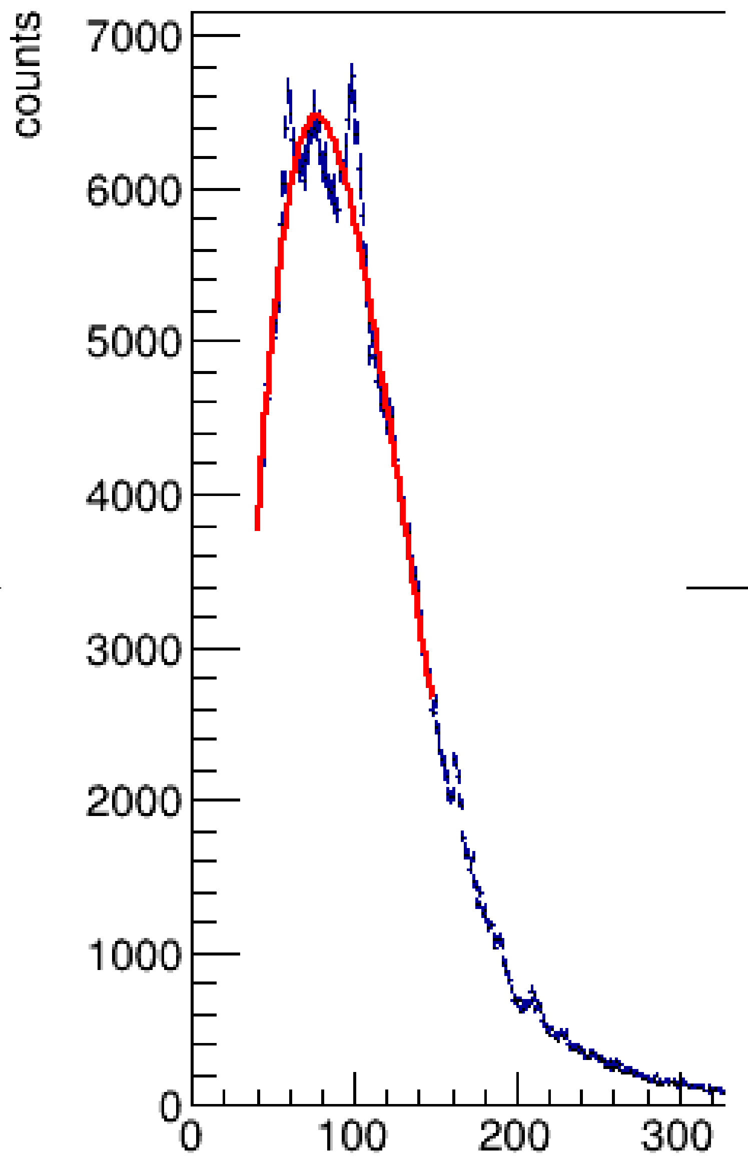


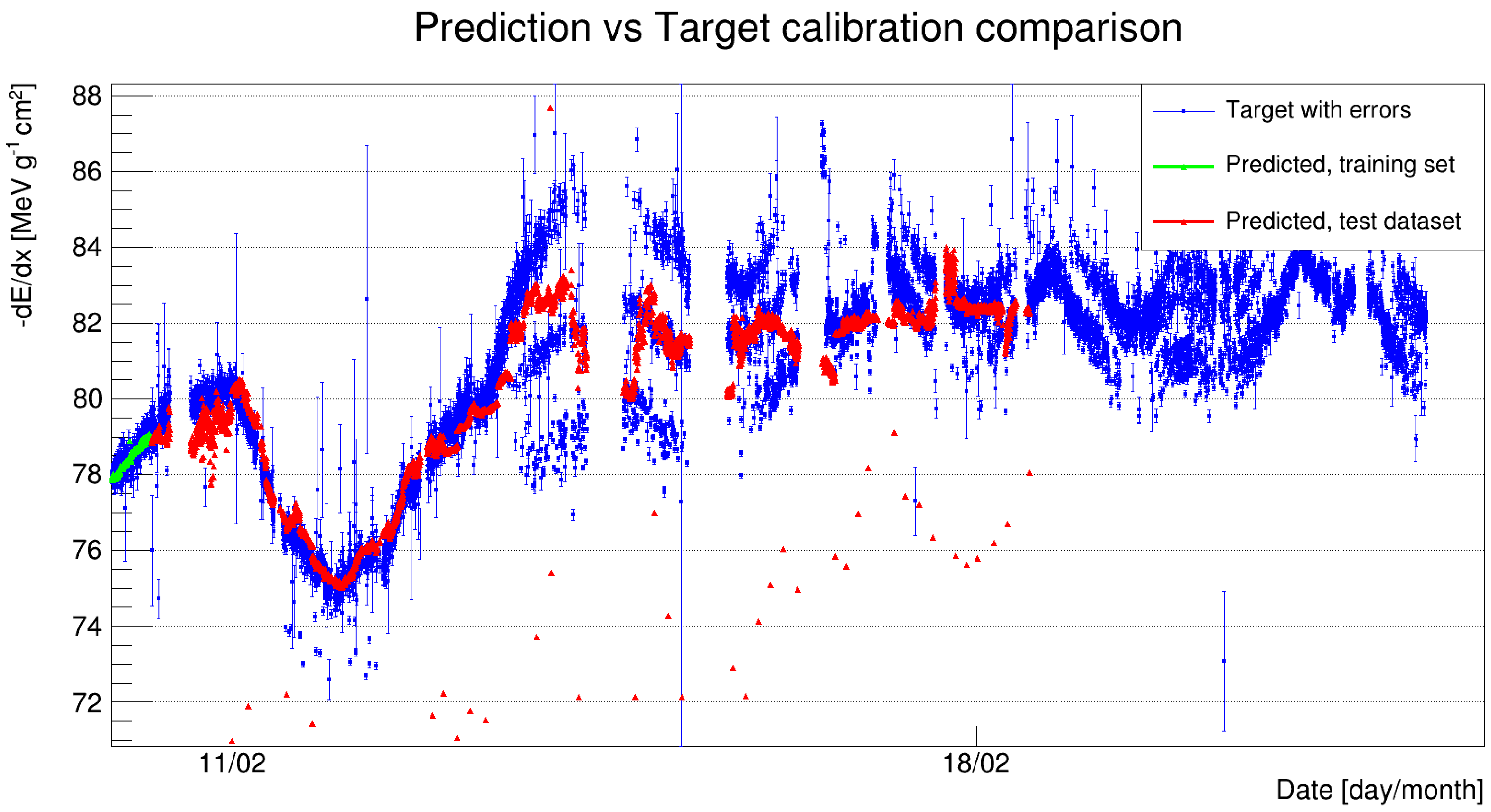
Further improvements in prediction quality

- Target calibration is far from perfect: wasn't done properly for each run at Hades.
- No temperature information. Importance of it was shown in different studies.

There is a room for improvements.







High voltage prediction x_i

(General) Training procedure if we have data with varied HV:

1. Train the model f. Fix parameters.

2. Train model G using $|f(X_{i-1}x_i) - Y_c|$ as loss.

$$f(X) = Y$$

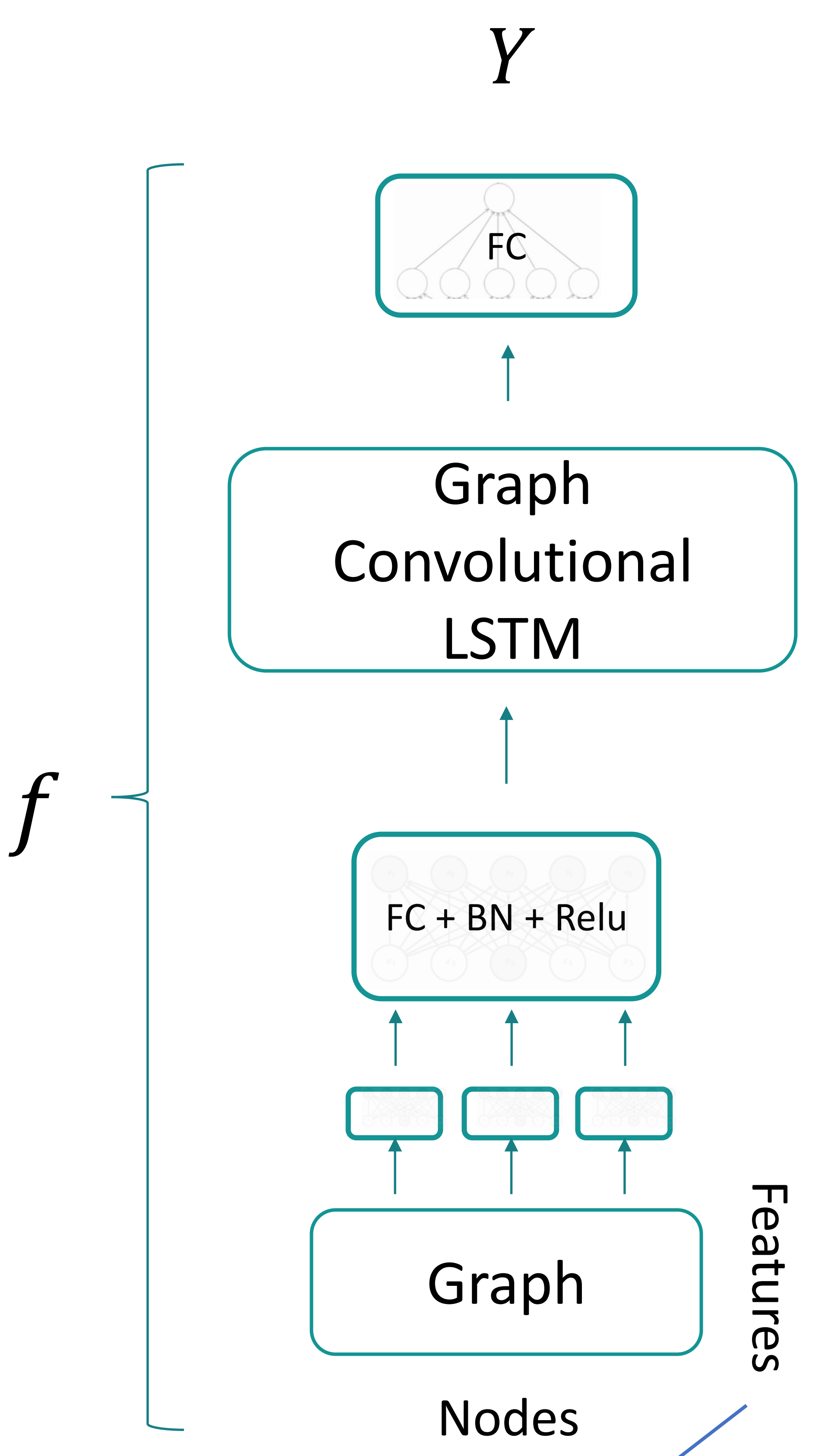
$$G(X_{i-1}|Y_c) = x_i$$

Sources of generating HV dataset:

1. Vary HV during cosmic runs.

2. Generate data with Garfield.

Multi-channel prediction



$$X = X_{i-1}x_i$$

Statistics accumulation is possible this year! (~December)

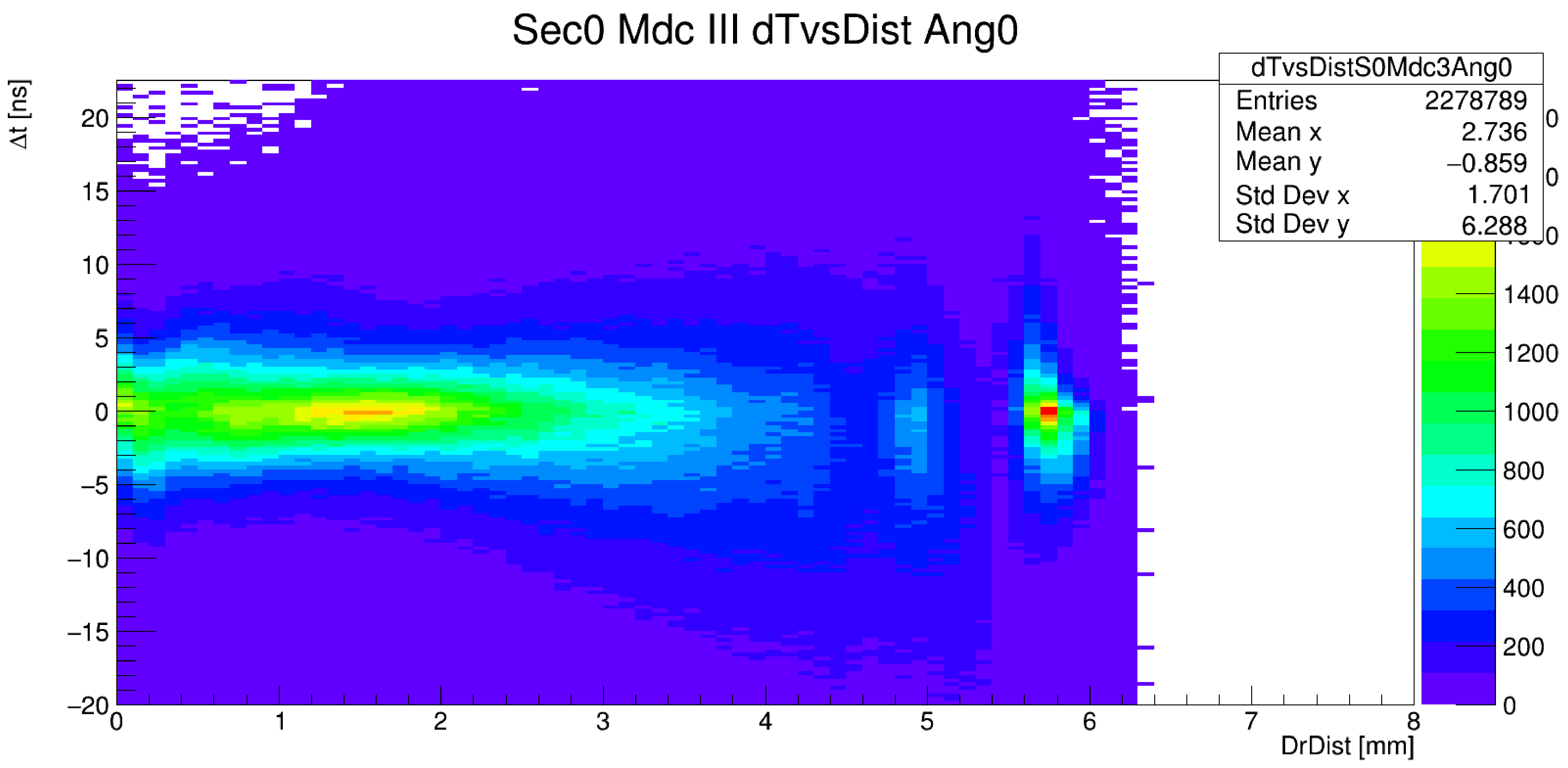
Summary & Outlook

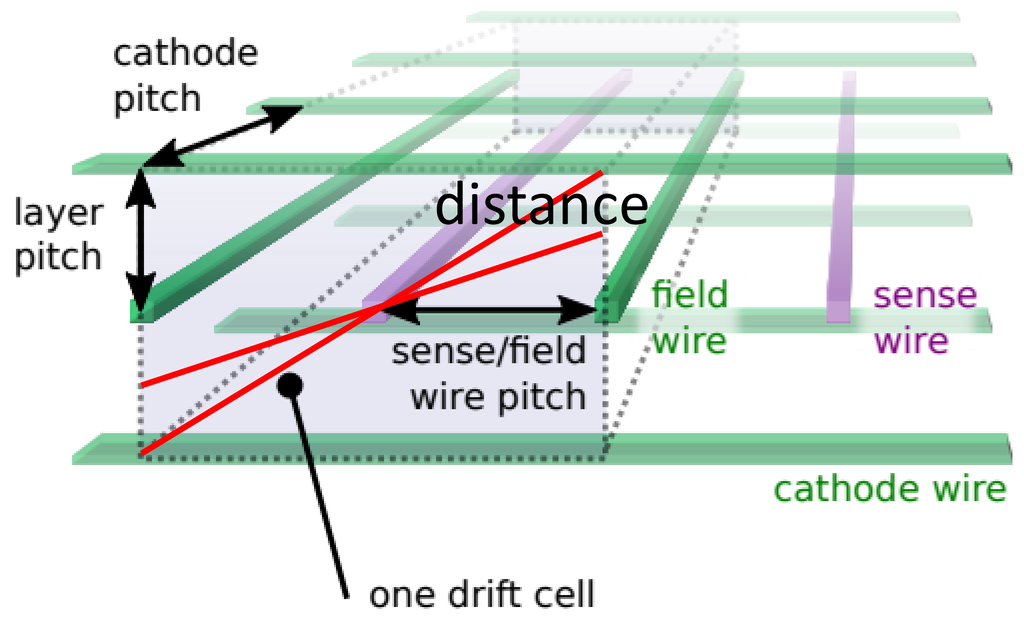
1. The method can provide fast (<1s) calibrations with accuracy, compatible with usual methods.
2. Predictions can potentially have smaller spread, but can be less reliable if done without care.
3. Very good precision with HADES MDC is possible, if offline calibration is improved.
4. Coding-wise, the program is ready for automatic work.

- Improvement of offline MDC dE/dx calibration.
- Test of predictions on the MDC time-distance calibration.
- Fine-tuning of the procedure for CBM usage.
- Varying of the HV during cosmic and HV predictions.

Backup

Overview of different calibrations



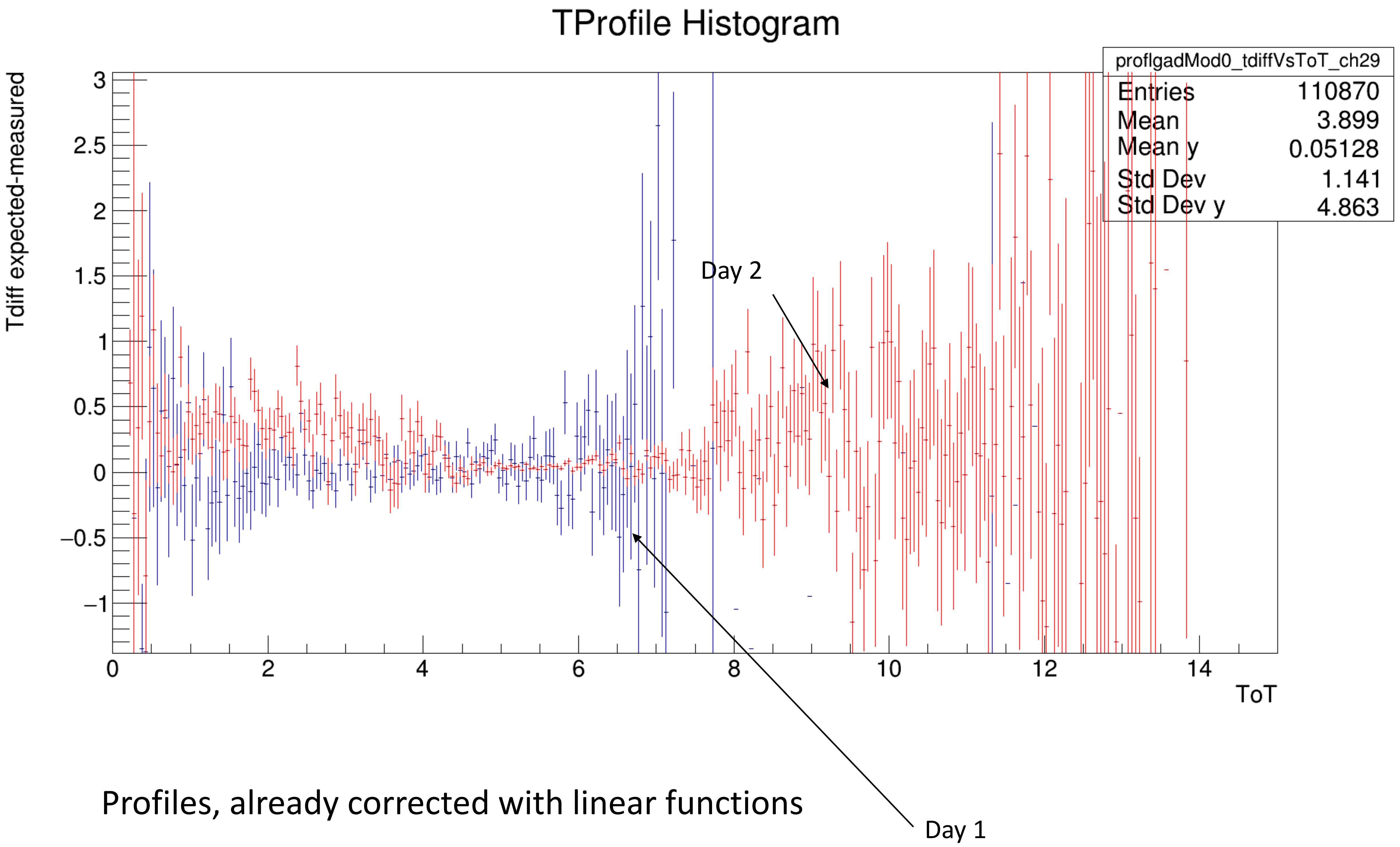


- Drift time – distance. Electronics (offset, tdc etc) and drift velocity. Calibrated initially with Garfield, after that iteratively corrected with data.

- Stored as a table sector, module, angle, distance – drift time.

  Can be possible to calibrate with NN if one reduces this to few parameters: module-sector as nodes, angles as input parameter. Target as parameters of fitting function. Or just both of angle and distance as input parameters and then fill the table with them.

Overview of different calibrations



Profiles, already corrected with linear functions

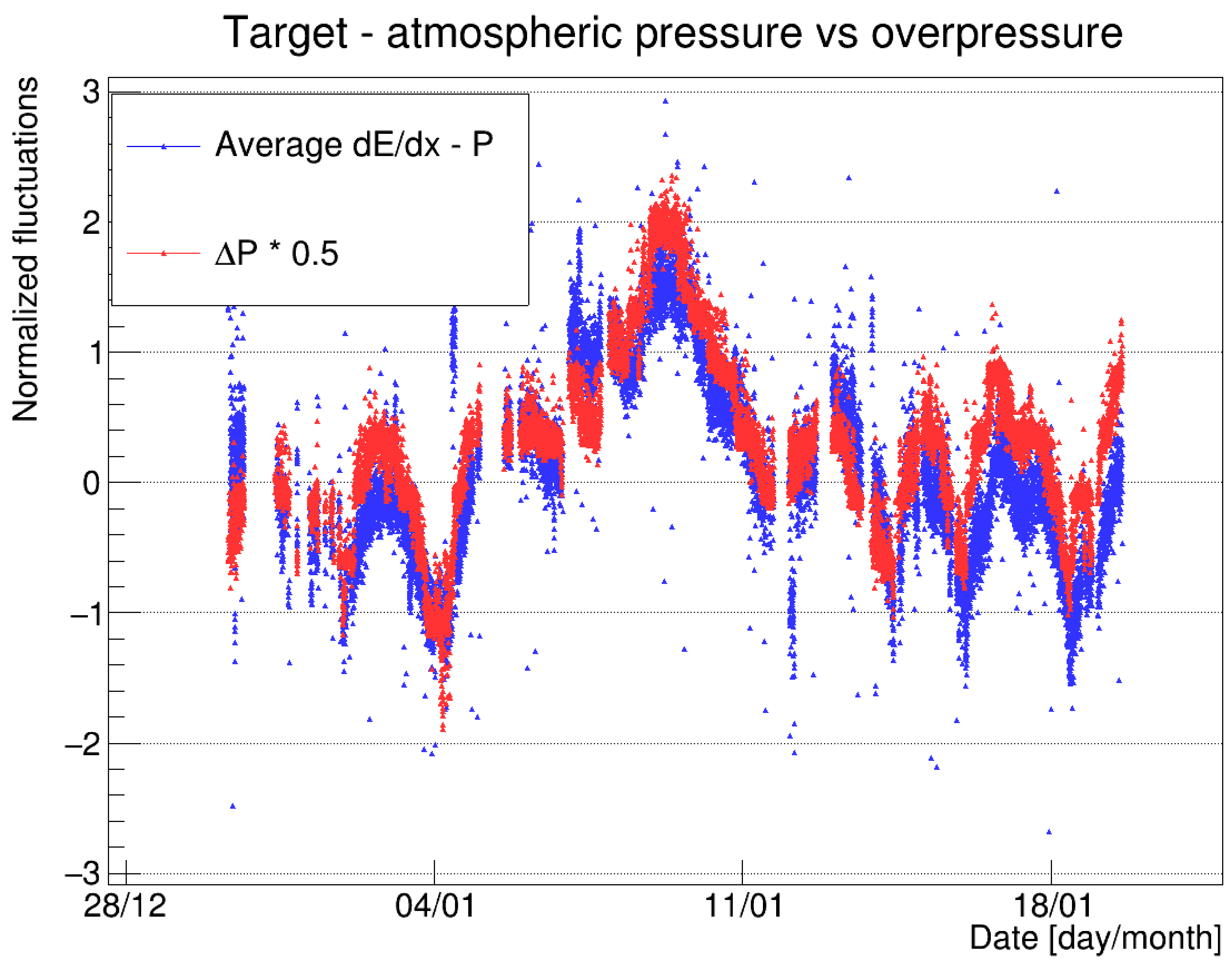
- T0 LGAD. Reconstruct events, calculate expected T0 from other ToF detectors. Correction of time-walk with a linear function of a profile, which appears from the fits in each bin.

- Problems for existing hades are at low values, where statistics is low and has nonlinearities in time-walk. Too low statistics to make it even as a target – bad application of NN

Ionization losses in drift chambers

Reasons to test on MDC:

- Significant fluctuations (5-10%);
- Clear dependence on environmental parameters;
- A lot of environmental parameters being measured.



Correlations between overpressure (red) and ionization losses, corrected on atmospheric pressure (blue). Feb22.

Each dot is a single run, ~100k/24 events, 1-2 min

Smooth change with time (~15 min).

Input parameters:

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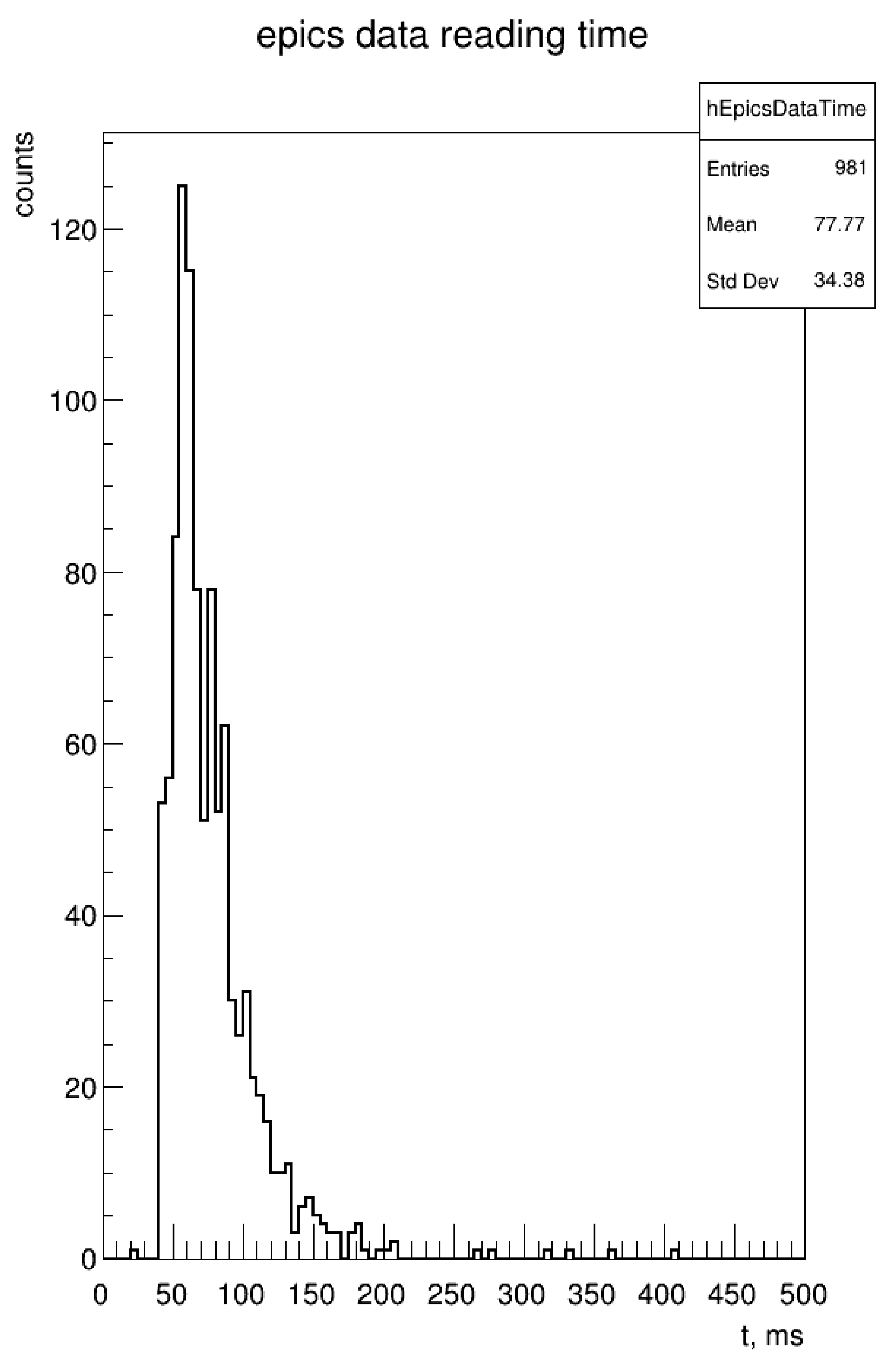
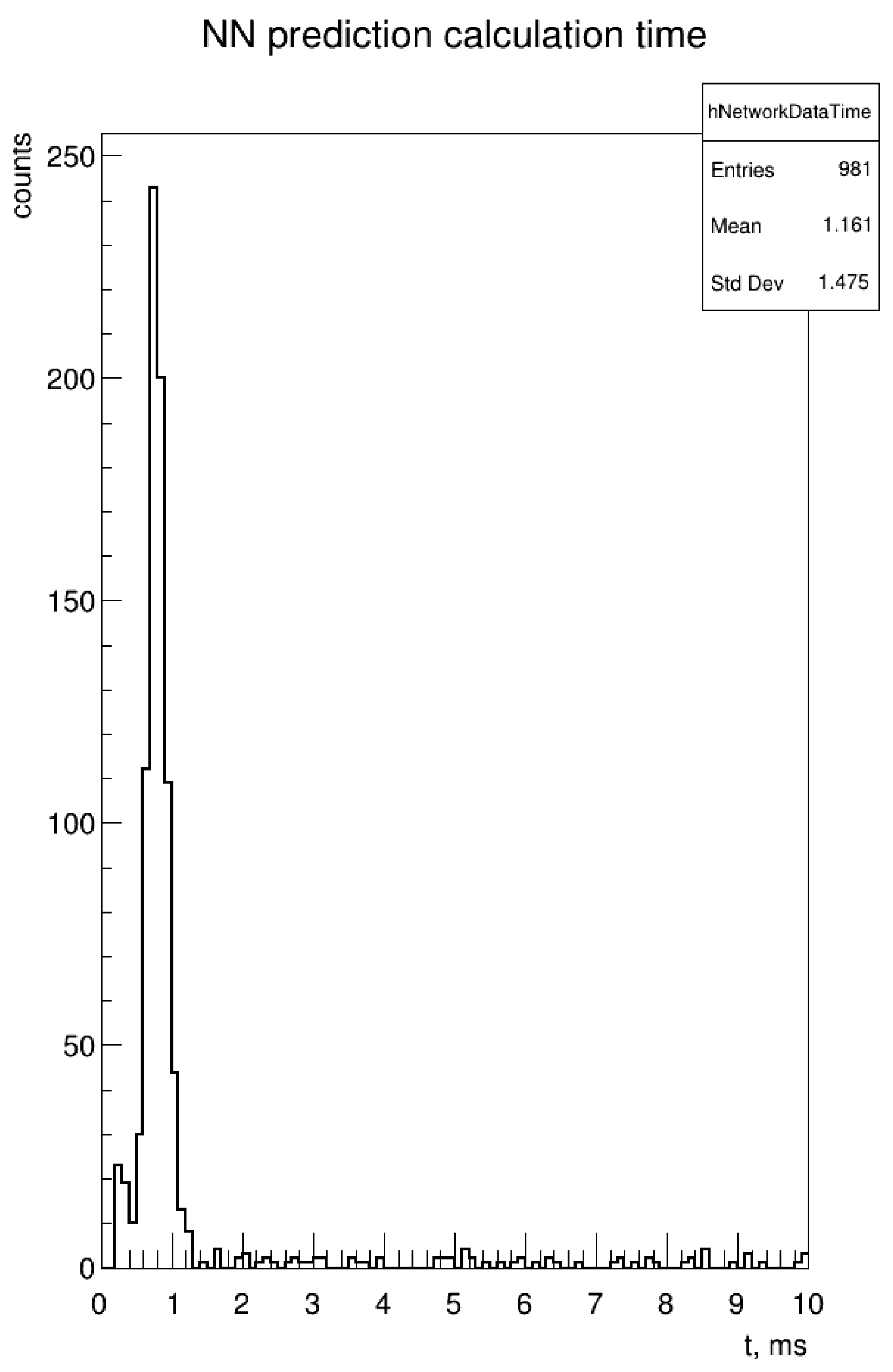
- CO_2 concentration;
- Overpressure;
- H_2O concentration;
- Dew Point;
- Electronics temperature;

Prediction time consumption

Single parameter, simple network

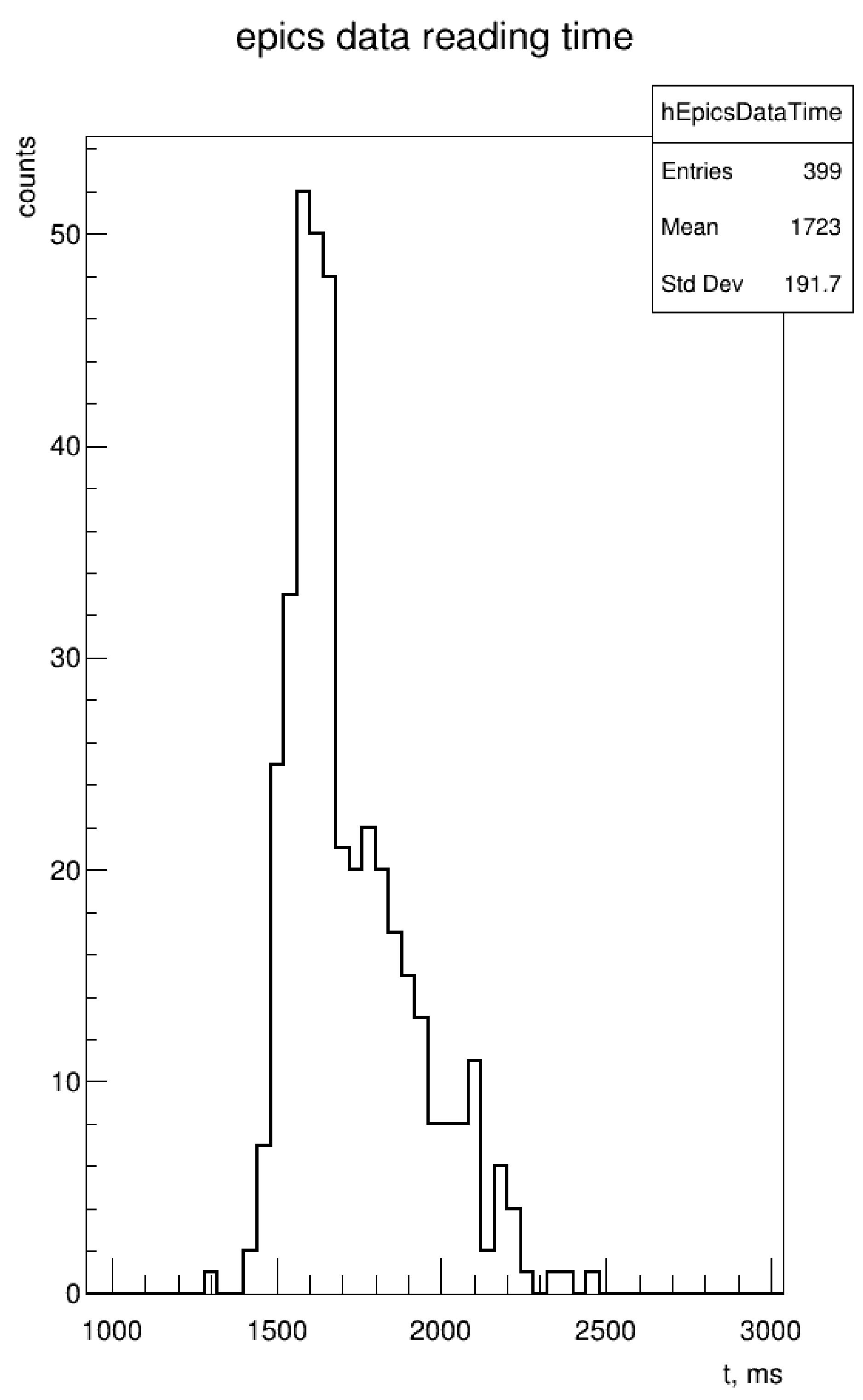


From GSI network

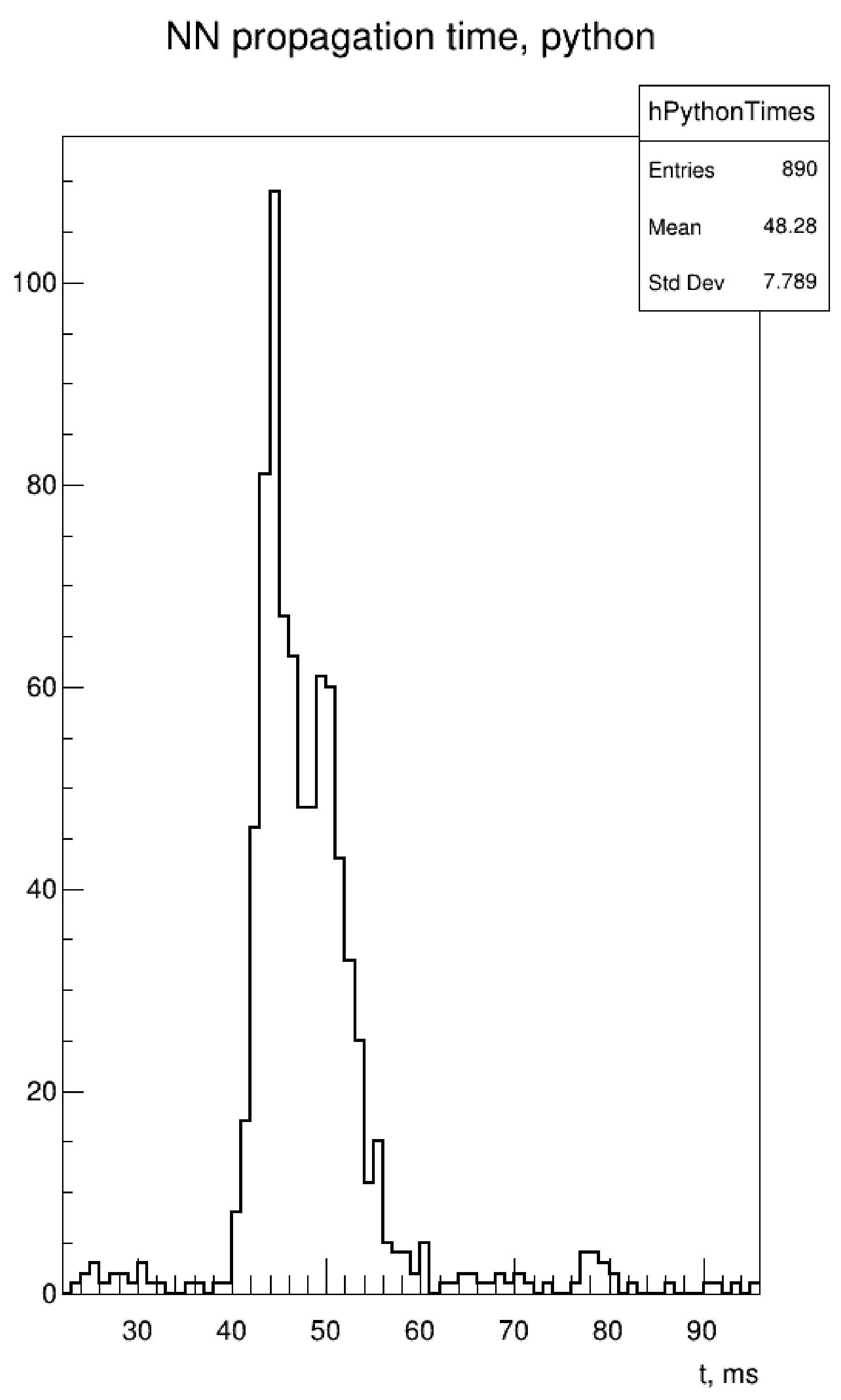


I7-1265U 10 cores 400$

24 parameters, GConv



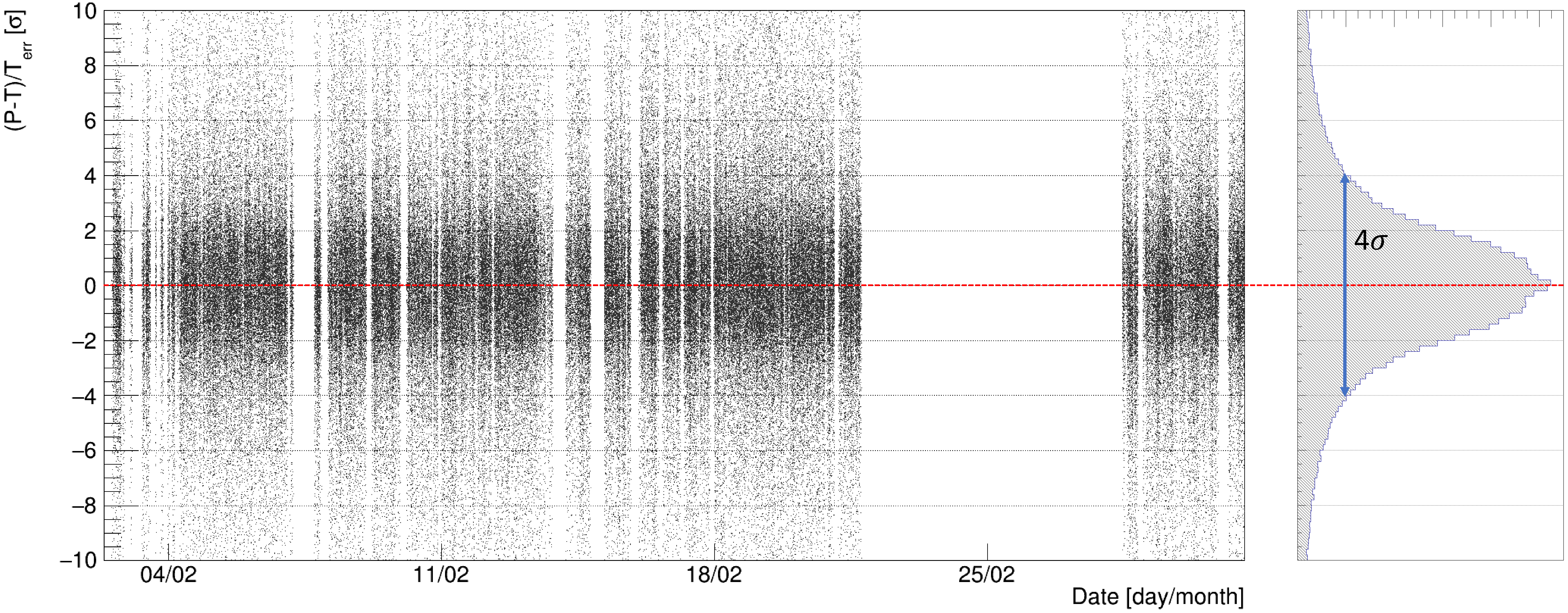
Wi-Fi, 50 MB/s



I7-1265U 10 cores 400$

Prediction Accuracy (training part)

$(\frac{dE}{dx})_{prediction} - (\frac{dE}{dx})_{target}$ in terms of calibration error σ



- Stable performance over the beam time.
- Compatible with target, the errors are underestimated.

Software development

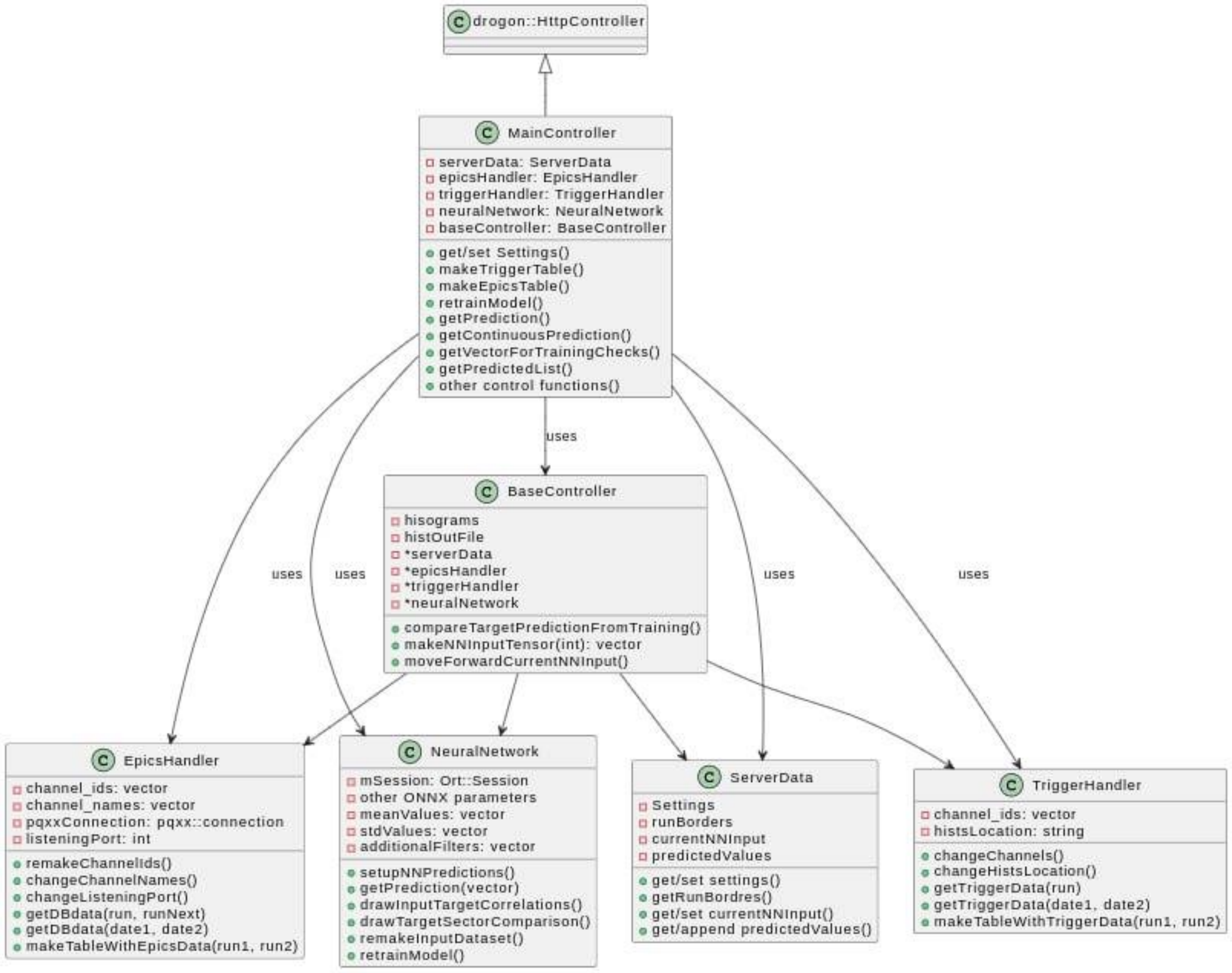
https://github.com/KladovValentin/drogonapp

Features:

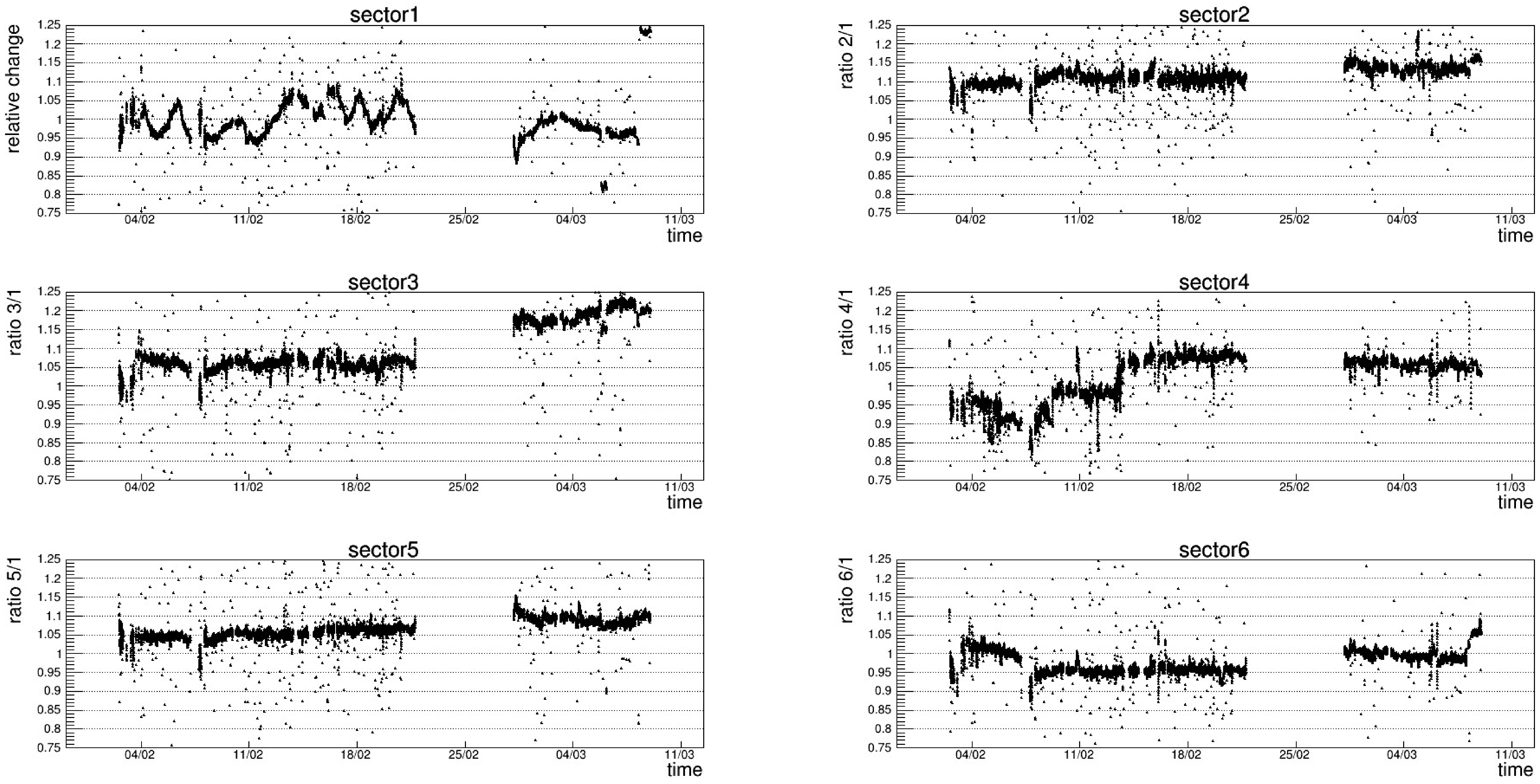
- Retraining with automated hyperparameter search.
- Automatic training set creation with given:
  - Epics channel names.
  - Trigger channel numbers and DQ files location.
  - List of runs, run borders or experimental files directory.
- Methods to save and change above settings + saves of NN data.
- Automated work with epics database:
  - connection,
  - conversation names-numbers,
  - handle missing data,
  - nn part of input on demand for run / list of runs.
- Automated work with trigger DQ files in the same way as for epics.
- Various methods to check training performance and correlations.

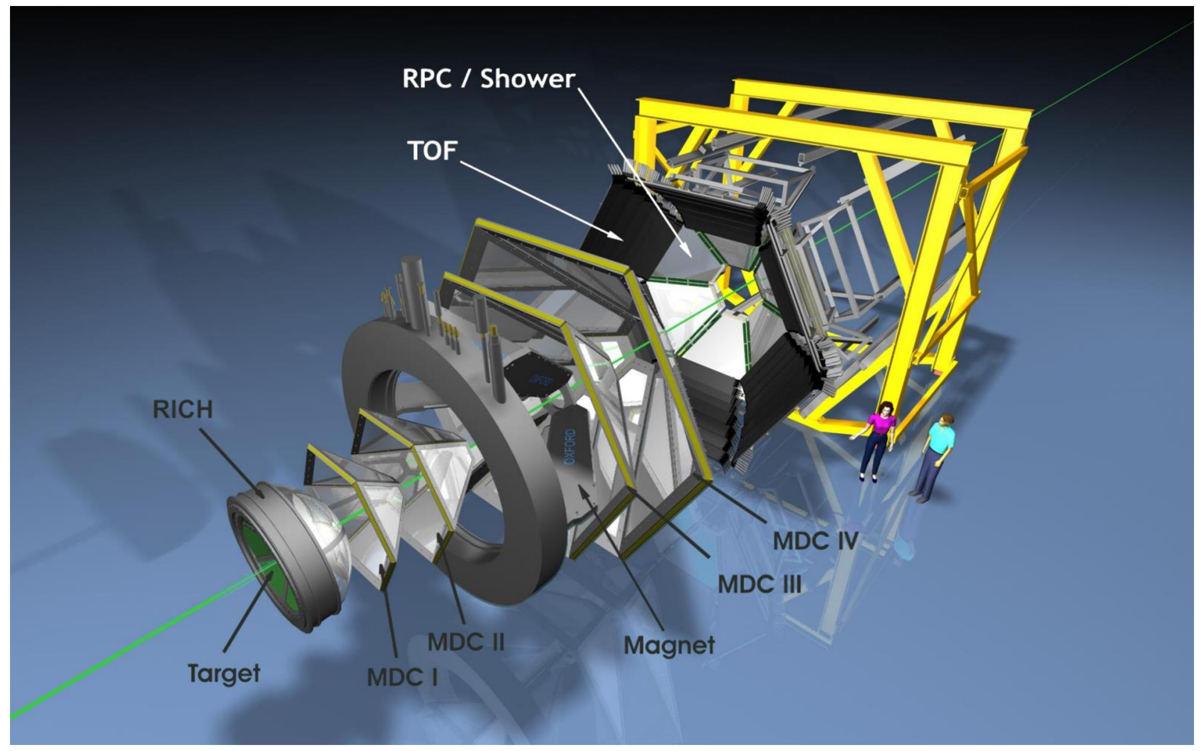
Methods:

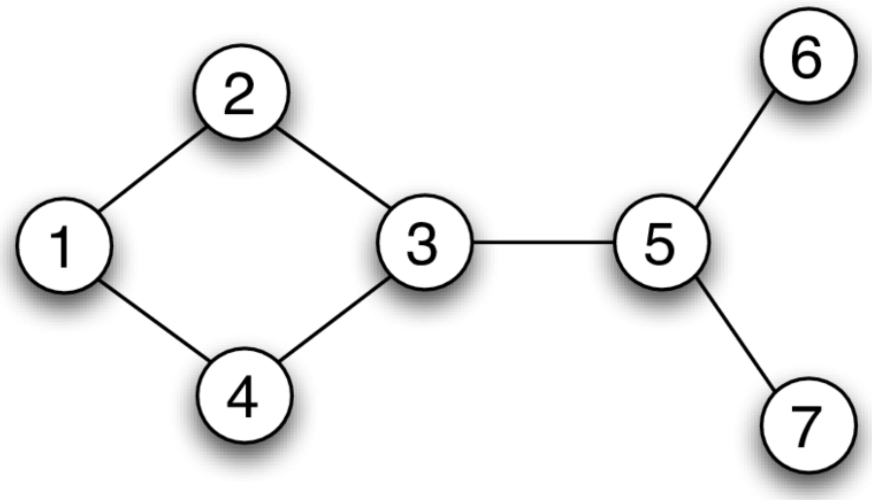
- Based on C++ and object-oriented programming paradigm.
- Epics db reading with SQL commands.
- Trigger data reading and graphics with ROOT CERN.
- NN training with pytorch in python and predictions in C++ with ONNX.
- Backend written in Drogon framework for C++.
- Frontend with react.js (little for now).



Multi-channel prediction







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